in **binary classification**, your model is deciding between **two options** — usually called **Positive** and **Negative** (like "spam" vs. "not spam").

🎯 Precision

Precision answers:

"When my model says *Positive*, how often is it actually right?"

It's about **how accurate your positive predictions are**.

Example:

If your spam filter marks 10 emails as spam and 8 really are spam,

👉 Precision = 8 / 10 = **0.8 (80%)**

So, high precision means **few false alarms**.

🔍 Recall

Recall answers:

"Out of all the real *Positives*, how many did my model find?"

It's about **how many true positives you caught**.

Example:

If there are 20 spam emails total and your filter caught 8,

👉 Recall = 8 / 20 = **0.4 (40%)**

So, high recall means **you found most of the actual positives**.

⚖️ The Trade-Off

- If you **raise precision**, you become more cautious (fewer false positives) but might **miss some true ones** → lower recall.
- If you **raise recall**, you catch more positives but might **get more false alarms** → lower precision.

Quick Analogy

Imagine fishing:

- 🎣 **Recall** = how many total fish you catch out of all the fish in the lake.
- 🧺 **Precision** = how many things in your net are actually fish (not boots or cans).